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BRIEF COMMUNICATION

Using home monitoring technology to study the effects of traumatic brain injury in older multimorbid adults

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Abstract

Internet of things (IOT) based in-home monitoring systems can passively collect high temporal resolution data in the community, offering valuable insight into the impact of health conditions on patients' day-to-day lives. We used this technology to monitor activity and sleep patterns in older adults recently discharged after traumatic brain injury (TBI). The demographics of TBI are changing, and it is now a leading cause of hospitalisation in older adults. However, research in this population is minimal. We present three cases, showcasing the potential of in-home monitoring systems in understanding and managing early recovery in older adults following TBI.

Introduction

Inexpensive in-home monitoring technology can be used to monitor the health of patients in their own homes.[1–3] These systems can passively capture millions of observations over extended durations providing insight into the effects of health conditions on patients' daily lives.[3–6] This is unachievable with traditional research or clinical approaches, which rely on patients attending infrequent assessments in lab or hospital settings. Sensor data can be used to derive indicators of health and function by analysing patterns and quantifying levels of activity and sleep.[3,4,7] These 'digital biomarkers' can be used to track progression of health conditions, and better target support from health and social care teams. Passive sensor systems require no user engagement, so have utility in groups where cognition affects insight or compliance.

The prevalence of traumatic brain injury (TBI) among older adults is increasing faster than other age groups, primarily due to falls.[8] Despite this older adult are underrepresented in TBI studies.[9,10] Therefore, much is assumed, but little is known about how TBI affects this population.[10] It is increasingly apparent that age alone is not synonymous with poor outcomes and factors such as pre-morbid multimorbidity and frailty influence recovery.[11,12]

We present a case-based analysis of activity and sleep data collected using a sensor system installed in the homes of three older adults with moderate–severe TBI (Mayo criteria).[13] We show how this data can provide insight into the effects of TBI in older adults and highlight the clinical potential of this technology.

Methods

We recruited inpatients aged ≥60 with moderate–severe TBI from a regional trauma centre. The Mayo criteria[13] was chosen to ensure inclusion of patients with definite TBI. Exclusion criteria included profound extracranial injury. This was a sub-study of Minder (run by the UK Dementia Research Institute Centre for Care Research & Technology), which uses in-home sensors to monitor older adults living with dementia.

Within 3 weeks from hospital discharge, sensors were installed in patients' homes for 6 months. To monitor changes in patterns of activity, passive infrared sensors (PIRs) (Fig. 1) were placed in rooms patients used most often. A pneumatic bed mat (Fig. 1) under the patient's

side of the mattress was used to measure time in and out of bed in conjunction with PIR data as a metric of sleep activity.

Participants and study partners were called weekly to corroborate any changes in activity or sleep. This enabled us to correlate PIR and bed mat data with health-related events and overall recovery. Assessments of frailty, cognition and function were performed at study entry, 3 weeks and 6 months (Fig. 3).

Data analysis

Changes in participants' patterns of activity and sleep (post TBI) were mapped by plotting PIR and bed mat activation over time using Python (Fig. 3). The weekly average for overnight activity per room was calculated using the total number of PIR sensor activations from each monitored room. A room was deemed to have abnormally high overnight activity if its weekly average activity was >2.5 standard deviations above the participants post TBI baseline, calculated as the average overnight activity from the first 4 weeks. Data were provided to consenting patients' healthcare teams if requested but was not available in real time.

The study has ethical approval granted by the London – Camberwell St Giles Research Ethics Committee (REC number: 17/LO/2066).

Results

Case descriptions

P1 is a 68-year-old retail worker, who was injured in a collision with a cyclist, sustaining a left-sided subdural haematoma (SDH) with mass effect (). She experienced contralateral visual disturbance, leg weakness and vertigo, as well as higher cognitive dysfunction, with deficits in attention, memory, verbal fluency and visuospatial processing.

P1 lives with multiple chronic health conditions but is not frail (Fig. 2). She reported an excellent recovery (Fig. 2), returning to an active social life and part-time

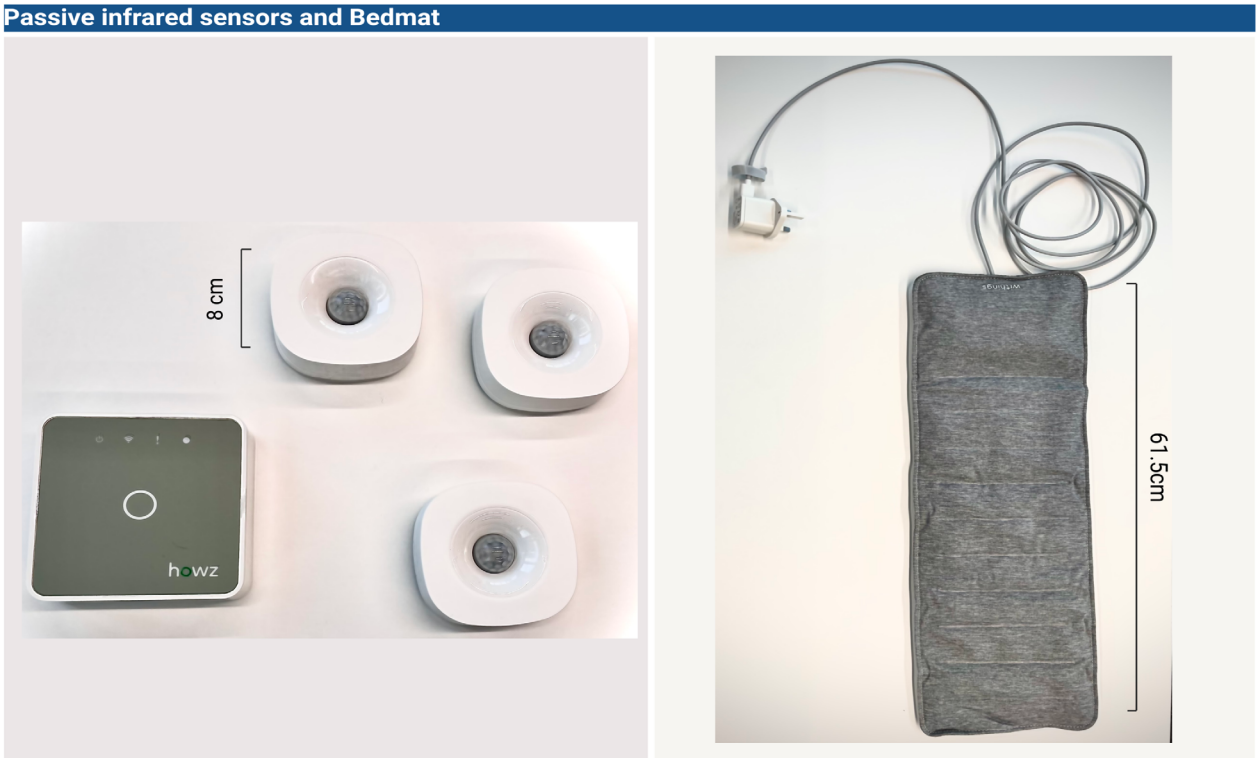


Figure 1. The passive infrared sensors (PIR) (A) measure light temperature and heat. They sense movement up to 9 meters away from the sensor with a view angle of 45 degrees up/down and left/right.[22] In our study, we obtain maximum sensitivity at around 3 m and have set the 'off-time' to 30 sec (sensors detect the prescence or absence of motion every 30 sec). The Withings bed mat (B) passively captures minute-by-minute heart rate, respiratory rate and movement using pneumatic sensors. The bed mat is waterproof and is placed out of sight underneath the mattress. The mat was developed in collaboration with sleep physicians at Hôpital Béclère and validated against polysomnograph.[23]

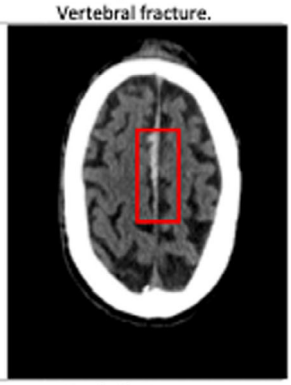
	Participant 1	Participant 2	Participant 3
Sex	Female	Male	Male
Age (at TBI)	68	87	97
Mechanism of injury	Pedestrian versus Bicycle	Fall standing height	Fall standing height
Extra-cranial injury details	No extracranial injury	Fracture of right clavicle	Non displaced C7 Vertebral fracture.
CT Head			
CT scan description & Marshall score:	Marshall: IV Left tentorial and parafalcine subdural haemorrhage with depth of 11mm, associated mass effect. Old lacunar infarcts noted in the basal ganglia.	Marshall: II Slim left sided cerebral convexity subdural haematoma. Mild sulcal effacement but no significant mass effect.	Marshall: II Shallow right parafalcine subdural haematoma, no mass effect. Age related cerebral involution. Moderate burden of microangiopathic disease.
Past medical history:	*Neurological:* Ischemic Stroke *Non neurological:* Aortic aneurysm repair Hypertension Hypercholesterolemia	*Neurological:* *none* *Non neurological:* Pancreatic cancer (operative treatment) Pancreatogenic diabetes Prostate cancer Recurrent prostatitis Hypertension B12 deficiency	*Neurological :* Mixed Alzheimer's vascular dementia *Non neurological :* Recurrent falls Chronic thrombocytopenia Hypertension Ischaemic heart disease Aortic valve replacement Permanent Pacemaker Heart Failure
Antiplatelet or anticoagulant medication	Clopidogrel	Nil	Aspirin
Charlson Comorbidity index	3	9	7
MOCA (at entry to study)	24	26	13
MOCA (at study exit/6 months)	29	30	15
Rockwood frailty (at entry to study)	2	4	5
Rockwood frailty (at study exit/6 months)	2	4	7
Barthel Index (at time of TBI)	100	100	80
Barthel Index (at study exit/ 6 months)	100	100	65
6-month GOSE	8	8	4
Total number household members	1	2	2

Figure 2. Demographic, injury and clinical information for patients. Montreal Cognitive Assessment (MOCA). Extended Glasgow Outcome Scale (GOSE).

employment. Her account of her recovery aligns fully with the observations from the home monitoring sensors. For example, her return to work has been mapped clearly in the PIR and sleep mat data from Week 12 (Fig. 3A). Bedroom, bathroom and kitchen activity is noted at 6 am followed by no PIR activation after leaving the house on workdays (Fig. 3A Week 12).

P2 is an 87-year-old retired healthcare professional who fell from standing. He presented 12 days later with dysphasia and unsteady gait. His CT demonstrated a small left-sided SDH (Fig. 2).

P2 has a high burden of comorbidity (Fig. 2) and, according to current literature, may have been expected to perform poorly following his TBI. However, he reported a good recovery from his injury (Fig. 2), resuming premorbid activities including holidays abroad (Fig. 3B Week 6–8). His reported recovery is corroborated by swift resumption of consistent patterns of daily activity throughout the house and time in bed, as captured by the sensors (Fig. 3B). Of note, in Week 9, P2 had a chest infection requiring antibiotics, during which the bedroom overnight activity was abnormally high (bedroom Week 9 PIR count = 12.1 vs. baseline bedroom PIR count = 8.0). However, there remained consistent daytime and overnight activity and sleep patterns, with no increased time spent in bed 'recuperating' (Fig. 3B Week 9), consistent with P2s resilience to acute illness.

P3 is a 96-year-old retired businessman who also fell from standing. His CT head demonstrated a parafalcine SDH (Fig. 2), and he experienced delirium whilst in hospital.

P3 had recently been given a probable diagnosis of mixed Alzheimer's and vascular dementia. Over the 6-month study, his sleep and behavioural disturbances worsened, necessitating increased care (Fig. 2).

P3 reported good sleep but the PIR and bed mat data indicated otherwise (Fig. 3C). Disruptions to sleep and circadian rhythm are common after TBI, but typically improve with time.[14] However, P3s data paint a picture of worsening sleep disruption after hospital discharge. Frequent night-time movements can be seen across multiple rooms not usually accessed at night, for example, office, consistent with overnight wandering. (Fig. 3C Week 5–8). For example, weekly overnight office activity is abnormally high over Weeks 5–8 (office Week 5–8 PIR count range = 10.1–14.2 vs. Baseline office PIR count = 5.9), There was also abnormally high weekly overnight lounge activity from Week 14 (lounge Week 14–27 PIR count range = 1.7–8.3 vs. baseline PIR count = 0.3), corresponding to when he started sleeping in the lounge. These behaviours were corroborated by his wife's reports.

Discussion

We showcase three cases of older adult TBI, whose post-discharge period was monitored with an in-home sensor system. We demonstrate that this technology can provide high temporal resolution insight into the effect of TBI in older adults. By mapping and quantifying changes in patterns of activity and sleep over time it may be possible to derive 'digital biomarkers' of clinically significant behaviour such as night-time wandering.

Limitations included challenges disarticulating data belonging to specific individuals in multi-occupant households. However, the activity of home occupants is interdependent and changes to an individual's health will affect the activity patterns of the entire household.[15,16] The availability of pre TBI data would increase sensitivity to detecting stable poor sleep patterns, however we were still able to detect clinically relevant deterioration, as seen with P3, even within these limitations. In addition, a single metric of sleep activity was derived from the PIR and bed mat; time in and out of bed and did not include other metrics of sleep quality such as stages of sleep. Limitations of the study are discussed in greater detail in our study protocol.[17]

P3's case highlights the utility of passive monitoring in patient groups where impaired insight affects recall. By monitoring the changes in levels and patterns of bed mat and PIR activity over time, we mapped the progression of his nocturnal behavioural disturbance, more accurately than by self-report alone. Sleep disturbance[18] and poor cognition[19] are independent risk factors for falls. Indeed, P3's carers reported five falls during the monitoring period. Making 'digital biomarkers' of behaviours that increase falls risk available in real-time to health and social care teams as part of 'hospital at home' or 'virtual ward' services could enable the swift initiation of interventions to address a patient's specific care needs (e.g. a bed exit alarm, adjustments to medications) whilst also monitoring their impact.

The data provided by the sensors combined with self-reported recovery emphasises that age alone is a poor predictor of prognosis. Age, multimorbidity and frailty do not always co-exist[20,21] and the recoveries of P1 and P2, who are older and multimorbid but not frail, exemplify this point. Larger controlled trials using monitoring technology could help further define the relationship between frailty, multimorbidity, age and the impact of TBI.

In summary, we show that data collected from inexpensive sensors can map changes in patterns of activity over time and could be used to derive 'digital biomarkers' that offer clinically meaningful insights into the effects of common health conditions, such as TBI. Such systems and 'digital biomarkers' can be used to track health

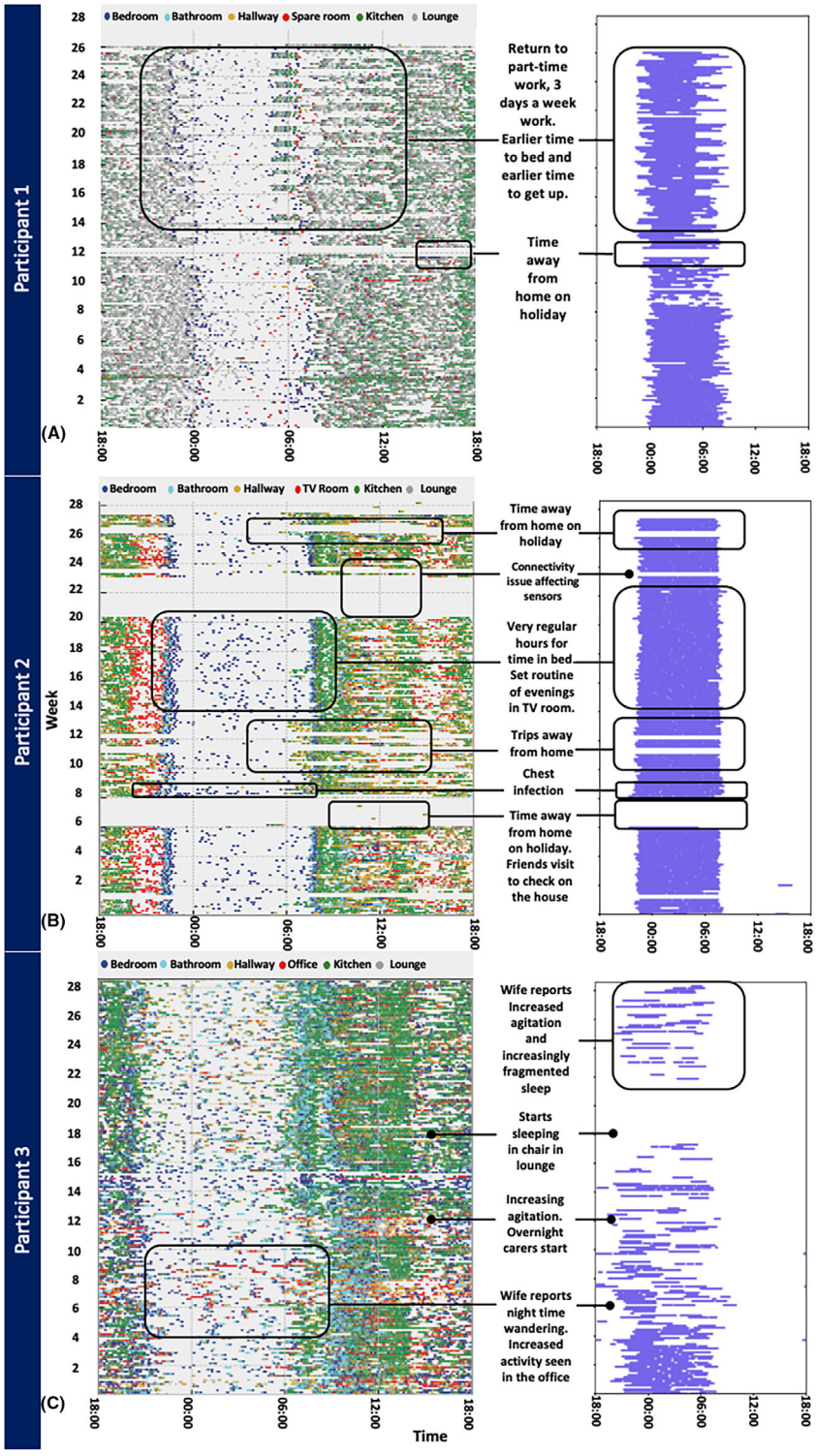


Figure 3. The figures above show 6 months of data passively obtained from infrared sensors (PIRs) and the Withings bedmat. The top three diagrams show data from the PIR sensor. Each dot represents movement activating a sensor. The different colour represents sensor activation in different rooms. The y axis shows the week and x axis shows the time of day. The figures are annotated with information obtained from a weekly phone call with the participant or carer. The bottom three raster plots demonstrate bed occupancy, that is, time spent in bed. The y axis shows the week and x axis shows the time of day.

conditions and effects of interventions in the community, with utility in vulnerable populations where insight is impaired.

Author Contributions

LML, MEP, MD, MF, DJS, PB and UK DRI CR&T conceived and designed the study. LML, MEP, RD, HL, ES, PB and AIS contributed to data acquisition and analysis. MEP and LML wrote the manuscript. MEP, HL and ES prepared the figures. Members of the UK DRI CR &T Research Group have all contributed to the development and ongoing management of the Minder system used in this project.

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Disclaimer

The views expressed are those of the author(s) and not necessarily those of the NIHR or UK DRI as a whole.

Conflict of Interest

We have no competing interests to declare.

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